Early Warning System of Landslide Disaster using Generalized Neural Network Algorithm

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***Abstract*—Landslides are frequently happened Indonesia, as many as 274 districts / cities are prone to landslides. There are many parameters that affect the landslide occurrence such as rainfall, land slope, soil moisture, and vibration. It is needed to provide a system that not only able to process data parameters to provide early warning of landslide disaster, but also increase the readiness of the population to minimize losses caused by this disaster. Generalized Regression Neural Network method is used to identify the effect of each parameter on the occurrence of landslide disaster. Tests conducted on field conditions and simulations in safe, alert, and danger condition to know the calculation result of artificial neural network. The simulation results are compared with the artificial neural network feed forward back propagation and manual calculations to demonstrate the effectiveness of the proposed method. The validation test on field condition using simulation shows average error of Generalized Regression method and Feed Forward Backpropagation method are 0.00115 and 0.08702, respectively. Furthermore, the Mean Square Error performance of the former method is better than that of the latter with values of 2.9157e-06 and 0.0112, severally.**

Keywords— Neural Network, Generalized Regression, Feed Forward Backpropagation, Landslide

I. Introduction

Indonesia is located on the Pacific Ring of Fire and the meeting point of four large tectonic plates of the world, this causes Indonesia to have a high intensity earthquake events. Indonesia also has a tropical monsoon marine climate with high rainfall character[1]. High rainfall causes increased water content in the soil, coupled with the vibration of the soil will facilitate the triggering of landslides. According to data released by the National Disaster Management Agency (BNPB), Indonesia has 274 districts / city with potential for landslides. In addition, there were 2006 landslide events have occurred in the regions of Indonesia during January 2017-July 2019[2].

The previous research on identification of parameters that affect the occurrence of landslide disaster has been studied in [3]. This study used the image processed topographical and geological data using geographic information system (GIS). Some factors were selected such as topography slope, soil type, rainfall, land cover as a landslide occurrence factors. These factors were analyzed using backpropagation neural network to generate the landslide susceptibility map. However, this study was not intended to identify landslide disaster potential in real time

The research of identification of landslide causation parameters in real time has previously been studied in [4], [5] and [6]. These studies used the parameters of rainfall, soil slope, and soil moisture with artificial neural networks Feed-Forward Backpropagation (FFBP) method as a decision-making system. However, the research don't include vibration as the cause parameter of landslide, and if the same method of Artificial Neural Network (ANN) is used with additional parameter will cause decreasing accuracy of ANN output.

Problems from previous research can be reviewed in this research using rainfall parameter, slope of soil, water content in soil at two different depth, and vibration as reference of early warning system of occurrence of landslide disaster. In this study we apply Generalized Regression Neural Network (GRNN) method as decision support system. It is expected that this research can provide better decision accuracy in giving warning of status of landslide risk condition in a region whether it is safe, alert, or danger.

The rest of this paper is organized as follows. In the Section II, we describe the detail of GRNN algorithm. In next section, the parameters of landslide which are considered in our research. In Section IV the results of designed system and discussions are provided. And then followed by conclusions in the last section.

II. Generalized Regression Neural Network

A. Artificial Neural Networks

ANN is an intelligent system model that is inspired by the biological system of the nerves, as in the process of information in the human brain. ANN has a good ability to get information from complicated data, able to solve problems that are not structured and difficult to define, and can learn from experience.

In general, ANN has three layers: input layer, hidden layer, and output layer [7]. To this date there are more than 20 methods of ANN. Each method has and uses different architecture, activation functions, and calculations in the process. ANN has capability such as classification, pattern recognition, forecasting, and optimization. The ANN has some models such as: Adaline, LVQ, Backpropagation, Adaptive Resonance Theory (ART), Neocognitro, Hopfield, Boltzman, and others.

B. Generalized Regression Neural Networks

D.F. Specht proposed GGRN algorithm [8], which is a kind of radical basis neural networks (RBF). The algorithm consists of input layer, pattern layer, summation layer, and output layer. These four layers are shown in Fig. 1.

The first layer admits information from input vectors and then directly forward them into pattern layer. Furthermore, the amounts of neurons in the input layer are same as the dimension of the input vectors in the learning sample. The number of neurons is same as the number of learning. Furthermore, the pattern of Gaussian function is written as follows.

$$P_d = e^{-\frac{(x-x_i)^T(x-x_i)}{2\sigma^2}} \quad (1)$$

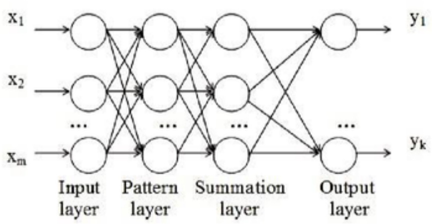

Fig. 1. Architecture of the GRNN model

There are two types of summation in the summation layer [9]. The first is mathematical summation, called S_S, and the second is weighted summation, called S_W. The functions can be written as follows.

$$S_s = \sum_{d=1} P_d \quad (2)$$

$$S_w = \sum_{d=1} w_d P_d \quad (3)$$

where w_d is the weight of pattern neuron i connected to the summation layer. As for output layer, the number of neurons is same as the number of output vectors y. The main function of GRNN model is written as following equation.

$$E[Y|X] = \frac{\int_{-\infty}^{\infty} Y f(Y,X)dX}{\int_{-\infty}^{\infty} f(Y,X)dX} \quad (4)$$

where X is an i dimensional input vector, Y is the prediction of GRNN. $f(Y, X)$ is the joint probability density function of Y and X. the E[Y|X] is the mean value of Y while the input vector X is given.

The GRNN algorithm has only one parameter σ that needs to be specified. Furthermore, we should create an automatically efficiently mean for choosing the proper parameter σ.

With strong ability of nonlinear mapping and flexible network structure, as well as high robustness and fault tolerance, GRNN is proper for solving nonlinear problems. And it has been widely applied to various fields including prediction, regression, and classification, such as in predicting traffic flow [10], cloud security intrusion detection [11], grading tobacco leaves [12], calorie prediction [13], performance of reluctance motor [14], etc.

III. Early Warning on Landslide Detection

In this study, several parameters are used as a reference of landslide disaster condition for the early warning system. Among the parameters above, four parameters have been used in this research including slope, rainfall, soil moisture,

TABLE I. LANDSLIDE PARAMETERS AND WEIGHTINGS

Parameters	Value	Weight (Score)	Value	Weight (Score)	Value	Weight (Score)
Slope	0-20	30%(1)	20-40	30%(2)	>40	30%(3)
Rainfall	0-30	15%(1)	30-70	15%(2)	>70	15%(3)
Soil Moisture	0-30	22%(1)	30-35	22%(2)	>35	22%(3)
Vibration	1-3	23%(1)	4-5	23%(2)	>5	23%(3)
Vegetation		10%(1)		10%(2)		10%(3)
Total		100%		100%		100%

and vibration. Parameter data that has been taken from sensor value scored 1-3 to determine conditions affecting the occurrence of landslide disaster. Vegetation parameters assumed to have a score of 2 because it is classified as an area analysis and unchanged in a short period of time. Then the parameters that have been scored multiplied by the weight that has been determined to get the results of landslide disaster condition value with the following formula:

Output = (BBx1 x 0,15) + (BBx2 x 0,3) + (BBx3 x0,11) + (BBx4 x 0,11) + (BBx5 x0,23) + 0,2 (5)

where BBx1 is the score value on the rainfall parameter. BBx2 denotes the score value on the slope parameter. BBx3 represents the score value on the soil moisture parameters at depth 1. BBx4 is the score value on the soil moisture parameters at depth 2. And BBx5 is the score value on the vibration parameter

IV. Results and Discussion

In this section we describe simulation results and the discussions. The results are obtained by performing simulations of GRNN and Feed-Forward Back Propagation (FFBP) methods.

A. *GRNN test on Obtained Field Data*

The test was performed to validate the GRNN by using simulations. The historical data used in this test was obtained directly from the sensor value, the data was taken and 10 samples are taken to test the output of ANN. The test was performed by analyzing the difference of output value from neural network Generalized Regression and Feed-Forward Back Propagation Neural Network which have been designed. Then the results were compared to manual calculation using (5). Table II exposes data from the taken test.

TABLE II. HISTORICAL SENSOR VALUE

No.	Rainfall (mm³)	Slope (%)	Soil Moisture 1 (%)	Soil Moisture 2 (%)	Vibration
1	0	1.22	56.07	7.70	0
2	0	1.23	55.17	7.59	0
3	0	1.12	58.38	7.46	0
4	0	0.93	54.57	7.67	0
5	0	0.13	54.13	7.84	0
6	0	0.8	56.12	7.66	0
7	0	0.99	55.82	7.01	0
8	0	0.85	55.06	6.72	0
9	0	0.75	55.24	7.57	0
10	0	0.65	56.42	6.70	0

TABLE III. OUTPUT COMPARATION ON HISTORICAL DATA

No.	Manual	Status	GRNN	Status	FFBP	Status
1	1.32	Safe	1.3200	Safe	1.2369	Safe
2	1.32	Safe	1.3200	Safe	1.2373	Safe
3	1.32	Safe	1.3200	Safe	1.2351	Safe
4	1.32	Safe	1.3292	Safe	1.2339	Safe
5	1.32	Safe	1.3223	Safe	1.2247	Safe
6	1.32	Safe	1.3200	Safe	1.2321	Safe
7	1.32	Safe	1.3200	Safe	1.2345	Safe
8	1.32	Safe	1.3200	Safe	1.2331	Safe
9	1.32	Safe	1.3200	Safe	1.2317	Safe
10	1.32	Safe	1.3200	Safe	1.2305	Safe

Furthermore, we analyze data output of GRNN and FFBP respectively, when compared to manual calculation, which is shown in Table III. After mathematical calculation, the results provide the average error 0.00115 and 0.08702, severally. The former has a better performance than the latter.

B. Safe condition simulation

The safe condition simulation was performed with various obtained values, which is shown in Table IV. Furthermore, the performance test was done by analyzing the difference of output value of artificial neural network Generalized Regression and Feed-Forward Backpropagation which has been designed with manual calculation using (5). The scores range that states the safe condition is from 1-1.69. The test was conducted with 10 experiments by varying the value of each sensor. Test results can be seen in the Table IV.

TABLE IV. SAFE CONDITION SIMULATION

No.	Rainfall (mm^3)	Slope (%)	Soil Moisture 1 (%)	Soil Moisture 2 (%)	Vibration
1	49	5	29	16	3
2	63	8	3	5	4
3	63	1	32	10	0
4	31	15	31	19	4
5	56	17	35	0	2
6	63	1	32	10	0
7	31	15	31	19	4
8	9	5	21	8	0
9	25	5	18	8	4
10	6	7	34	32	2

TABLE V. SAFE CONDITION SIMULATION RESULT

No.	Manual	Status	GRNN	Status	FFBP	Status
1	1.25	Safe	1.25	Safe	1.3218	Safe
2	1.48	Safe	1.48	Safe	1.5039	Safe
3	1.36	Safe	1.36	Safe	1.3307	Safe
4	1.59	Safe	1.59	Safe	1.5015	Safe
5	1.66	Safe	1.66	Safe	1.5500	Safe
6	1.36	Safe	1.36	Safe	1.3307	Safe
7	1.59	Safe	1.59	Safe	1.5015	Safe
8	1.10	Safe	1.10	Safe	1.0705	Safe
9	1.33	Safe	1.33	Safe	1.2899	Safe
10	1.32	Safe	1.32	Safe	1.2305	Safe

Table V exhibits calculation value of GRNN and FFBP with 10 data samples, respectively. Then we compare each result to when manual calculation that yields performance of average error with value of 0 and 0.05267, severally. The GRNN is superior than the FFBP in safe condition simulation.

C. Alert condition simulation

We perform testing for analyzing the performance of GRNN and FFBP methods in alert condition simulations, which is shown in Table VI. The test was conducted with 10 experiments by varying the value of each sensor. Then we obtain the results of test with score range in values between 1.7 and 2.39.

Table VII shows the output value of GRNN and FFBP respectively on 10 data samples, which are compared to manual calculation. Then we obtain the average error with value of 0 and 0.07248, respectively. The performance of the former is better than the latter in this situation.

TABLE VI. ALERT CONDITION SIMULATION

No	Rainfall (mm^3)	Slope (%)	Soil Moisture 1 (%)	Soil Moisture 2 (%)	Vibration
1	26	47	14	35	2
2	5	57	28	9	3
3	12	48	4	3	4
4	137	31	20	55	6
5	9	25	60	73	6
6	75	37	5	39	5
7	8	24	46	59	4
8	62	25	34	35	4
9	42	40	31	33	7
10	125	24	8	76	0

TABLE VII. ALERT CONDITION SIMULATION RESULT

No.	Manual	Status	GRNN	Status	FFBP	Status
1	1.81	Alert	1.81	Alert	1.8168	Alert
2	1.70	Alert	1.70	Alert	1.7478	Alert
3	1.93	Alert	1.93	Alert	1.7922	Alert
4	2.38	Alert	2.38	Alert	2.3437	Alert
5	2.30	Alert	2.30	Alert	2.1795	Alert
6	2.15	Alert	2.15	Alert	2.2343	Alert
7	2.07	Alert	2.07	Alert	1.9160	Alert
8	2.00	Alert	2.00	Alert	1.9578	Alert
9	2.23	Alert	2.23	Alert	2.2864	Alert
10	1.92	Alert	1.92	Alert	1.8777	Alert

D. Danger condition simulation

The test is done by analyzing the difference of output value of artificial neural network Generalized Regression and Feed-Forward Backpropagation which has been designed with manual calculation using (5). The scores range that states the safe condition is from 2.4-3. The test was conducted with 10 experiments by varying the value of each sensor. Test results can be seen in the Table VIII.

TABLE VIII. DANGER CONDITION SIMULATION

No.	Rainfall (mm3)	Slope (%)	Soil Moisture 1 (%)	Soil Moisture 2 (%)	Vibrati on
1	150	85	39	32	5
2	131	73	43	31	7
3	135	59	40	93	3
4	75	88	55	85	4
5	130	68	49	98	6
6	41	63	86	81	5
7	36	89	89	81	6
8	147	79	7	77	4
9	92	79	9	42	6
10	112	84	35	33	5

TABLE IX. DANGER CONDITION SIMULATION RESULT

No.	Manual	Status	GRNN	Status	FFBP	Status
1	2.56	Danger	2.56	Danger	2.5493	Danger
2	2.79	Danger	2.79	Danger	2.7643	Danger
3	2.44	Danger	2.44	Danger	2.4753	Danger
4	2.67	Danger	2.67	Danger	2.5379	Danger
5	2.90	Danger	2.90	Danger	2.8924	Danger
6	2.52	Danger	2.52	Danger	2.5584	Danger
7	2.75	Danger	2.75	Danger	2.6327	Danger
8	2.45	Danger	2.45	Danger	2.5372	Danger
9	2.68	Danger	2.68	Danger	2.5835	Danger
10	2.45	Danger	2.45	Danger	2.5019	Danger

Then, the same procedure is also performed by comparing manual calculation result to the output values of GRNN and FFBP respectively on 10 data samples, see Table IX. By using mathematical calculation, it delivers average error performance of the both methods are 0 and 0.06288, respectively. It implies that the former is better than the latter, again.

E. Overall performance

Overall performance of GRNN and FFBP are compared by using both Regression and Mean Squared Error that has been taken from training data simulation. GRNN have better performance on this study, shown by R value that is closer to 1 and lesser MSE value, as shown in Table X.

TABLE X. OVERALL PERFORMANCES

	R	MSE
GRNN	1	2.9157e-06
FFBP	0.9566	0.0112

V. CONCLUSION

Early detection of landslides is done by identifying parameters of rainfall, slope, soil moisture, and vibration. GRNN is used to identify the effect of each parameter on landslide disaster and provide early warning condition which is safe, alert, or danger. The results are proved that GRNN had more advantage in fitting and prediction compared with FFBP neural network. The simulations results show that the accuracy of GRNN output is better than that of FFBP output. Further data retrieval on the actual landslide condition is required to obtain more accurate identification of landslide causation parameters, with MSE value of 2.9157e-06 and 0.0112, respectively.

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